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Improving Out-Patient Flow at An Indian Ophthalmic Hospital

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ABSTRACT

In the recent past, Healthcare sector has shown an exceptional growth all over the world. At the same time, rising health consciousness among patients and demand for quality services has resulted in a stiff competition among hospitals. Consequently, hospitals are increasingly focusing on improving the operations to meet the requirements of patients. To meet this requirement, hospitals need to improve and redesign their existing processes. In this mission of redesigning the healthcare systems, simulation modelers have an important role to play. Simulation modelers can help hospitals in delivering high quality healthcare by proposing strategic scenarios that work in synchronization with operations management philosophies. In this study, we extend an effort in this direction by showcasing the use of simulation as a modeling and analysis tool at an Indian ophthalmic hospital. In particular, we model the outpatient department with a goal of achieving a streamlined patient flow. We analyze various scenarios to compute the adequate resources, while maximizing their utilization. This study results in significant reduction in service lead time, especially in the circumstances where every extra minute spent add to the vows of patients and their aids.

Keywords: *healthcare, process improvement, simulation modeling, discrete-event simulation*

1. INTRODUCTION

Providing quality Healthcare has become a worldwide goal. Healthcare services pose unique challenges due to its intrinsic nature of intangibility, time-sensitivity, urgency, and high levels of customer involvement. Healthcare providers have become increasingly interested in curbing their costs and improving service quality from the last two decades (Boyer & Pronovost, 2010). The result has been the development of new process improvement practices aimed at enhancing the quality of patient care, while reducing costs, increasing patient satisfaction, eliminating medical errors, and improving clinical efficiencies.

Most common and important patient interface occurs in the outpatient department (OPD) of a hospital. Outpatient services are crucial because the profits obtained from them enable the hospital to offset possible losses on certain inpatient services and invest in new medical technologies. Thus, hospitals often treat the OPDs as profit centers with an aim to maximize revenue. In spite of the strong importance of outpatient services, hospitals generally face strong complaint about the disproportionately long time which patients are obliged to wait compared with the actual period devoted to medical examination, treatment or advice (Doyle *et al*., 1980). In Japan, it is often termed as *'waiting for three hours to be seen for three minutes'*. On the other hand, hospitals often allow the large queue of patients to build up in order to avoid the possibility of idleness of the consultant while waiting for a patient. Thus, balancing patient wait time and consultant idle time is a key strategic decision in an OPD. Starting from the early work of Bailey (1952), numerous researchers have investigated this issue.

The complaint about excessive patient waiting time in OPDs is widely observable. On humanitarian grounds, it is clearly undesirable to keep patients waiting longer than actually needed. At a broader level, it results in the loss of National working time, which most of the countries can ill afford given the present man-power shortage. On the other hand, consultant's time generally pertains to a fixed cost, which should be best utilized for maximizing revenue. In practice, therefore, full utilization of consultant's time is treated as an over-riding consideration by the hospitals. As a result, higher patient wait time lead to patient dissatisfaction and possible adverse clinical consequences, while higher consultant idle time lead to higher costs and underutilization of various resources. Thus, hospitals face a strong need to provide both the flow and cost-efficient OPD services to satisfy the continuously increasing patient expectations. In order to improve on these dimensions, the healthcare providers worldwide have to redesign their systems by adapting the best practices, tools, and processes (Natarajan, 2006). Importantly, the scope of such efforts is huge in India (Natchiar *et al*., 1994).

This paper contributes toward this end by showing, via an actual OPD study, that significant improvements in out-patient flow, consultant utilization, resource utilization and cost efficiency can be achieved as a result of proper resource leveling and streamlining of OPD processes. The setting for the paper is an ophthalmic hospital located in the Southern India, which provides OPD, surgical, and emergency services. Semi-charitable in nature, the hospital manages to provide low cost eye treatment to Below Poverty Line (BPL) patients. One of the major patients' grievance was the time they spend while waiting in OPD. The time a patient took from entering the OPD to see the consultant was long and highly variable. Overtime was a regular custom in the OPD, even then, few walk-in patients were being denied the appointments on weekends, resulting in significant goodwill and revenue loss. As a result, we faced a situation where the patient wait times and consultants' finish times were long and uncertain.

This paper develops a detailed simulation model of out-patient flow for an ophthalmic hospital to aid decision makers in identifying system bottlenecks and potential areas for improvement, with the objective to reduce both the patient wait times and consultants' finish times, while allowing the OPD to possibly see more patients. A variety of methods are used for patient flow improvement in hospitals (see, Cayirli *et al*., 2006; Guo *et al*., 2004; Day *et al*., 2010; El-Darzi *et al*., 1998; Mcfadden, 1996). However, discrete-event simulation models are extremely preferred for health applications due to their complex yet flexible features (see, Guo *et al*., 2004; Fetter & Thompson, 1965; Centeno *et al*., 2001; Chand *et al*., 2009). Interested users may refer to Cayirli & Veral (2003) for a comprehensive review. Furthermore, the main focus of most of these papers was patient flow control and improvement through the appointment scheduling (see, Natchiar *et al*., 1994; Cayirli *et al*., 2006). Distinct from previously developed models like Griffin *et al*. (2012), the key aim of our paper is to improve out-patient flow as well as resource utilization.

Discrete Event Simulation (DES) models have been applied extensively for planning and managing healthcare systems (Davies & Davies; 1987, 1995). In addition to DES, other methods for modeling health systems include: [i] Queueing theory and Markov systems (Weiss *et al*., 1982; Kozumi *et al*., 2005) [ii] An integration of queueing and simulation (Cochran & Bharti, 2006). These types of models are also employed for the study of scheduling policies in addition to patient flow.

Patient classification is extremely important when modeling healthcare systems. Many different methods are used for this purpose including the use of opinions from hospital experts and statistical or data mining techniques (Harper, 2002; Isken & Rajagopalan, 2002). Some key features found in other patient flow models include statistical fitting of length of stay (LOS) data (Marshall *et al*., 2005), including patient blocking (Styrborn & Thorslund, 1993), and examination of the paths assigned to the patients (McFadden, 1996).

Distinct from previously developed models, the model we present here better represents the full reality of an Indian ophthalmic system. With the methodology described below, we define and apply a robust and complete model, resulting in insights regarding the behavior of ophthalmic facilities under different situations and the value of implementing various scenarios to improve patient service. We demonstrate the outcomes from implementation of various capacity varying scenarios in practice, which is often lacking in health care simulation models (Brailsford *et al*., 2009).

2. PROBLEM SETTING

As identified through the discussions with patients, consultants, and staff (optometrists), the OPD was experiencing three major problems: (1) the patient wait times were high and variable, (2) overtime was a regular custom, and (3) long queues were being built at shared facilities (special eye-testing machines).

Hospital had a common registration desk for providing the appointments for OPD, surgical and emergency patients. During weekdays, an average of 70 patients were availing the OPD services. 30 slots were reserved for the patients booking their appointments through telephone one day in advance, and 40 slots for walk-in patients in a day. Average service demand was reaching up to 90 patients on weekends, but the OPD was unable to serve more than 75 patients even with an hour of overtime. Thus, appointments slots were limited to 20 on weekends. Even then, few walk-in patients were being denied service on weekends. This was resulting in significant goodwill and revenue loss. The patient no-show problem was nominal. Appointments to walk-in patients were given during 08:30 to 14:30 hours. The regular OPD timings were from 09:00 to 17:00 hours including a half an hour lunch break. After completing the registration, patients were sent to the central waiting area. OPD had no control over the registration processes, thus pre and post diagnostic processes are out of the scope of this study. Description of various personnel/facilities visited by patients are described below in their respective sequence.

2.1 Central Waiting Area

After completing the registration, patients wait in the central waiting area. They visit to the optometrist for preliminary diagnosis at a first come first serve (FCFS) basis. They have to wait in-between diagnostic steps, whenever required. Capacity of the central waiting area was more than enough, hence not a constraint.

2.2 Optometrists

Patients were sent to the optometrists for initial check-up. At the time of this study, 10 optometrists were dedicated for OPD operations. Optometrists were responsible for classifying the patients in three different categories (I, II and III) depending upon the case complexity and diagnostic requirement. Type I patient required simple routine checkup, while type III patients require extensive attention. **Figures 1**, **2** and **3** show a schematic representation of the OPD flow for each patient category based on path-based modeling approach. Each facility group is depicted as a rectangle, with the respective parenthesized count of the number of machines/personnel indicated within the square. The paths followed by the three types of patients moving through the hospital are also shown in these figures.

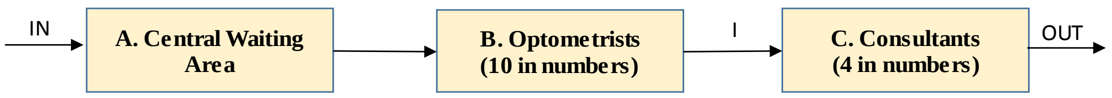


Figure 1 Schematic Flow of Type I Patients

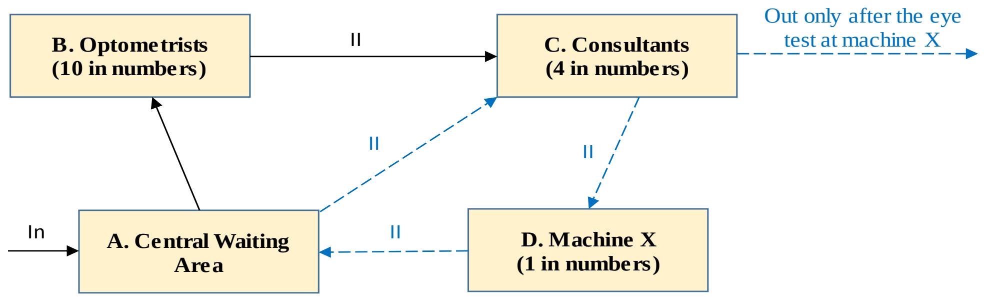


Figure 2 Schematic Flow of Type II Patients

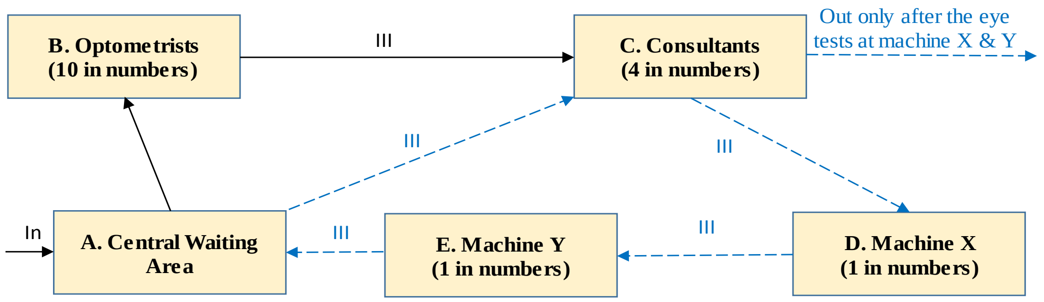


Figure 3 Schematic Flow of Type III Patients

As shown in **Figures 1-3**, standardized checkup sequence is in practice for each patient category. Visitation sequences of different patient categories are summarized in **Table 1** as below.

Table 1 Facility Visitation Sequence

Patient Category	Facility visitation sequence (from left to right)						
I	A	B	C				
II	A	B	C	D	A	C	
III	A	B	C	D	E	A	C

2.3 Consultants

Consultants were required to be involved in OPD, surgery or research on a particular day. 4 consultants were dedicated for the OPD. Category I patients leave the OPD after taking the consultation. While category II and III patient was directed to advanced eye testing machines as shown in **Figures 2-3** and then revisit the consultant.

2.4 Advanced Eye Testing Machines

Apart from the routine equipment used in eye tests, there were two types of advanced eye testing machines available at the hospital, machines X and Y (exact names and type concealed). As per the standardized checkup process, type II patients must go through eye test at machine X and type III patients must go through eye test at machine X followed by eye test at machine Y. Two separate rooms were dedicated for these machines, thus these are modeled as two different facilities. Hospital owns one machine of each type. Two machine operators were dedicated for these machines.

3. SIMULATION MODELING

Managers face decision-making situations every day. They have to choose the best course of action from a set of feasible alternatives. Implementation of a wrong alternative might cost significant money, time and efforts. These alternatives can be evaluated using simulation, without ever trying them out in the real world. Simulation also helps to analyze the current system performance and to evaluate the potential benefits from possible improvement strategies (Zuting *et al*., 2014). Thus, we find simulation as the best tool to address the present case. DES models the operation of a system as a discrete sequence of events. Each event corresponds to a particular instant in time. Whenever an event occurs, it marks a change in the state of the system. Between consecutive events, no change in the system is assumed to occur; thus the simulation can directly jump in time from one event to the next. Thus, we use DES to model the current state of OPD operations. The simulation model was implemented using GPSS world, which is an efficient tool to model a discrete system (Vlasov *et al*., 2014).

For developing the simulation model, we began by obtaining data to identify system characteristics including patient classification schema. We obtained 12 months of data from the electronic medical record system of the hospital to generate input for the simulation model. A first hurdle that had to be resolved was the quality of the data. It was found that some records were incomplete or incoherent; thus, those records were omitted. This process was verified by the hospital managers based on their expertise. Using the remaining quality data, we performed statistical analysis to establish values for patient interarrival times, different patient types, and average step times at different stages. It was determined that, 12% of the patients fall in type I category, 35% in II category, and the rest 53% in category III. The patient interarrival time are given below in Table 2, obtained using historical data.

Table 2 Patient Interarrival Time

Interarrival Time (minutes)	Relative Frequency	Cumulative Frequency
≤ 0	0	0
> 0 - ≤ 1	0.05	0.05
> 1 - ≤ 2	0.15	0.2
> 2 - ≤ 3	0.2	0.4
> 3 - ≤ 4	0.15	0.55
> 4 - ≤ 5	0.3	0.85
> 5 - ≤ 6	0.1	0.95
> 6 - ≤ 7	0.05	1
≥ 7	0	

Each patient's case is unique due to various medical factors, thus we expect step time to contain significant variations. This problem has been addressed by estimating distribution of step times based on the patients' category.

Step times for various personnel and facilities are summarized in **Table 3**, as given below. Cost parameters for revenue calculation are given in **Table 4**.

Table 3 Step Time for Personnel/Facilities

Personnel/Facility		Instance	Distribution of the Step Time (Minutes)		
			Patient Type 1 (12%)	Patient Type 2 (35%)	Patient Type 3 (53%)
A	Central Waiting Area	First Visit Revisit	Exponential (38.3) NA	Exponential (38.3) Exponential (27.6)	Exponential (38.3) Exponential (36.8)
B	Optometrist		Erlang (12.2,2)	Erlang (14.9, 2)	Erlang (21.3, 2)
C	Consultant	First Visit Revisit	Erlang (8.1, 2) NA	Erlang (6.7, 2) Erlang (7.8, 2)	Erlang (4.9, 2) Erlang (9.1, 2)
D	Machine X		NA	Uniform (8.2 ± 2.8)	Uniform (8.6 ± 1.3)
E	Machine Y		NA	NA	Uniform (7.6 ± 1.8)

Table 4 Cost Parameters

Revenue per Patient		Monthly Salary		Machine	X*	Y*
Registration	50	Machine Operator	7,500	Investment	5,00,000	7,50,000
Test X	10	Optometrist	10,000	Salvage Cost	25,000	50,000
Test Y	20	Consultant	24,000	Expected Life	12 months	12 months

***Straight line depreciation method is followed (all currency figures are in Indian Rupee)

Once all the logic factors were developed and coordinated, the model was first verified and later validated. Validation is the process of ensuring that the model truly represents the real world. Behavior of the model was observed by looking at the results and ensuring that the step times, utilization, number of patients per day, etc. gave reasonable results. Further, the simulation model was validated through the comparison of patient wait time, resource utilization, monthly revenue, and number of patients served per day with actual observations. To evaluate the steady state system performance with the simulation model, we ran 50 replications of 1 year time a 30 day warm-up period. Warm-up period is used to allow the queues to get into typical running conditions. Results are not collected during this period, so this also helps to reduce bias in the system performance measures. The number of replications was chosen to create tight confidence intervals on all measures of interest, such that the half-width is within 5% of the average.

The model was set up to gather data about the desired measures of performance. The measures of performance that were used in this study were:

- System Throughput (number of patients served per day)
- Service Lead Time (SLT)
- Average Non-Value Adding Time of the System (NVATS)
- Resource Utilization
- Net Monthly Revenue (NMR)

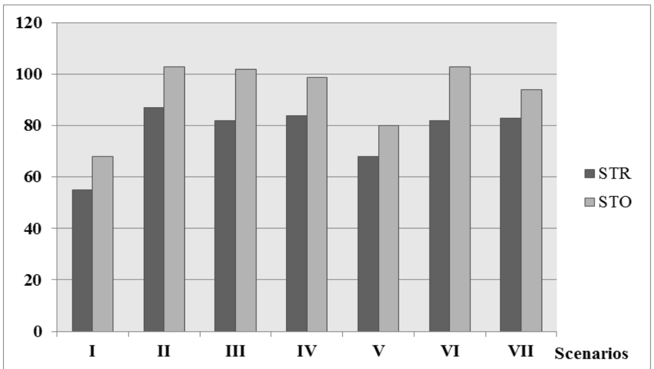
While this model was created to represent the conditions of an Indian hospital, the model could be adjusted to fit the operations of other countries.

4. RESULTS

We ran simulation model to depict the current state of the system (OPD). It was revealed by simulating the current state of the system, that facility D (machine X) was the system bottleneck. Its contribution in system's non-value adding was the largest among the five facilities. While giving due attention to various cost parameters, we along with the team of hospital managers, explored the possibility of various possible scenarios to improve the system performance. Apart from the current system state, six additional scenarios were finalized and modeled. These scenarios, generated from the discussions with hospital management; account for the main concerns of the OPD, depicting the operational differences between the current system and the system while managing bottlenecks. There might be some solution other than the developed scenarios, but that is not considered as feasibility and final decisions were left for managers' discretion. The scenarios modeled were as follows:

I. Current system state
II. Adding one machine of type X
III. Adding two machines of type X
IV. Adding both machines X and Y, one of each type
V. Adding one machine of type X and layoff of one consultant
VI. Adding one machine of type X and layoff of one optometrist
VII. Adding one machine of type X and layoff of two optometrists

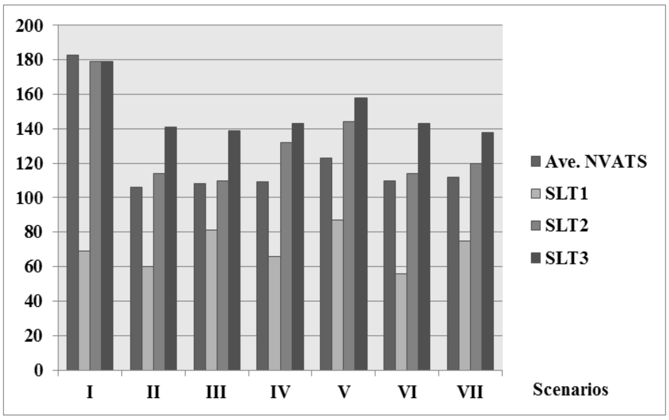
Performance characteristics were measured under each scenario. **Figure 4** shows the system throughput under proposed scenarios over the current state of the system. To depict the system state with overtime, in each scenario, system throughput has been modeled both for regular (ST_R) and overtime (ST_O) shift. It is clear from the figure that both the ST_R and ST_O are substantially improved in scenarios II and VI. Much likely, overtime can be avoided on weekdays by following any of the scenarios II, III or VI.



$\mathbf{ST_R}$ – System Throughput (regular 8 hours shift), $\mathbf{ST_O}$ – System Throughput (with 1 hour overtime)
Figure 4 System Throughput (Number of Patients Served per Day)

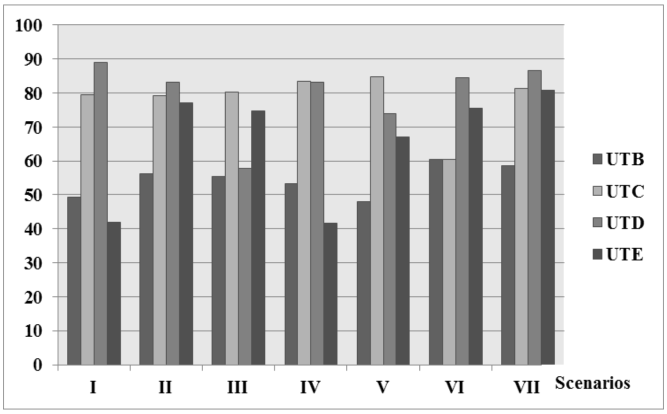
Figure 5 gives an overview of the Non-Value Adding Time of the System (NVATS) and Service Lead Time (SLT) experienced by different categories of patients under considered scenarios. SLT_1, SLT_2 and SLT_3 are the service lead time experienced by patients of category I, II, and III respectively. Each of the six proposed scenarios, shows significant improvement in NVATs over the system's current NVAT. Different scenarios leads different SLT for each patient category. Thus, they cannot be compared directly.

Figure 6 summarizes the results for utilization of optometrists, consultants, and machines X and Y. Facility A was kept out of this analysis, as its capacity will remain unconstrained, even if the demand is doubled. With a few notable exceptions, utilization rates are fairly stable across



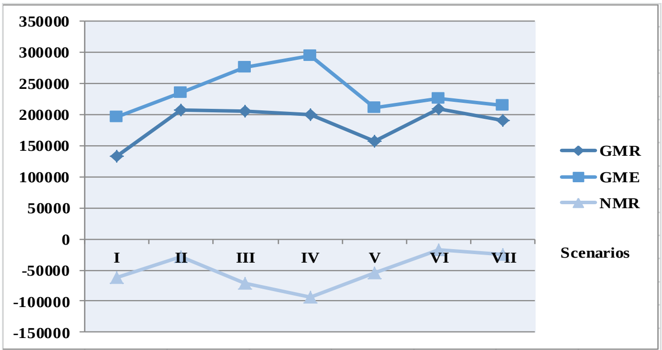
$\mathbf{SLT_x}$ – Service Lead Time (for patient category X), **NVATS** –Non-Value Adding Time of the System
Figure 5 Service Lead Time (in Minutes)

the scenarios. As expected, the blocking of facility E as seen in scenario I, reduced significantly after tackling with the starvation of initial system bottleneck (facility D), except in the scenario IV. Interestingly, the addition of second machine of type X (scenario III) makes the utilization of facility D lower, even with the same demand. This is what an important factor to consider while balancing the service lines (Fitzsimmons & Fitzsimmons 2006).



$\mathbf{UT_x}$ – Utilization of Facility X
Figure 6 Resource Utilization (%)

Considering the costs as given in **Table 4**, we calculated gross monthly revenue (GMR), gross monthly expenditure (GME), and net monthly revenue (NMR) of the OPD for all the seven scenarios. **Figure 7** shows these values. We can clearly see the fact that the OPD was running in losses for all the seven scenarios that were modeled. Still, being semi-charitable in nature, the major focus of the hospital was to improve the cost efficiency with the possibility of providing OPD services to more patients, rather than profit maximization as already noted in the introduction section. Though, loss minimization is one of the key management concern for self-sustainability of the hospital.



Scenario	I	II	III	IV	V	VI	VII
NMR	-77,800	-51,683	-100,566	-123,816	-76,283	**-39,583**	-46,683

GMR – Gross Monthly Revenue, **GME –** Gross Monthly Expenditure, **NMR –** Net Monthly Revenue

Figure 7 Monthly Revenue (in Indian Rupee)

Figure 7 shows that the scenario VI yielded the lowest cost, and it was certainly the most competitive alternative (based on NMR) when compared to all other scenarios. It suggested a cost reduction of 42.12% from the current state of the OPD. The results and suggestions presented to the hospital management were not complex, while considering the implementation phase.

5. CONCLUSION

Patients have become increasingly concerned about the non-value adding time they spend in a hospital. On the other hand, in practice, maximum utilization of consultant's time is treated as an over-riding consideration by many hospitals. To address this tradeoff, in this study, a simulation model focusing on out-patient flow at an Indian ophthalmic hospital was created and adapted in an investigation of potential system improvement opportunities. In the model, multiple categories of patients with different paths in the OPD were considered. A total of seven scenarios including then current state of the OPD were modeled and analyzed. Final suggestions depicted substantial improvements in the number of patients served, patient's waiting time, non-value adding time of the system, and resource utilization. OPD costs were expected to be reduced by 42.12%. Researchers opine that cost savings at different levels contribute towards the profit of entire supply chain network (Daultani *et al.*, 2015). These cost savings apply to almost every industry (Pettersson & Segerstedt, 2013). The problems in any part of the system might hamper the profit of the organization, resulting into supply chain risk (Vilko & Ritala, 2014). Hence, there is a lot of scope for operational improvement studies at various levels of a healthcare organization at various levels (Kritchanchai, 2012).

The literature supports the use of simulation modeling in a hospital setting. This paper adds further support to using simulation modeling and analysis for improving the out-patient flow, resource utilization, and operational as well as cost efficiency of an OPD. Distinct from the previously developed models, the problem environment in this study is an OPD of an ophthalmic hospital. This study takes care of many practical aspects, like patient classification, path based modeling approach for the patients of different categories, facility utilization, and various cost parameters. This model has the flexibility to be potentially adapted to OPD facilities at other hospitals. In summary, this simulation model can provide hospitals with the ability to measure and predict current and future system performance under different scenarios.

A limitation of the method used is the requirement of enough quality data to estimate the patient inter-arrival time, and step time of various personnel/facilities. This is dealt by obtaining the 12 months data from the electronic medical record system of the hospital and removing the incomplete entries to obtain the quality data. In addition, patient classification is given a due consideration to obtain a clear picture of the paths followed by the patient inside the OPD. The main limitation of the study is that the limited feasible scenarios as per the discussions with hospital managers were modeled and analyzed. There might be some optimal solution other than the seven scenarios, but that is not considered as feasibility and final decisions were left for managers' discretion. We recommend future work to examine the relationship between appointment and various scheduling policies for flow improvement. Also, in future work the model can be further extended to other hospital settings.

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